Does New Technology Impact Product Recalls?
An Empirical Examination in the Automotive Industry

by

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Abstract

As technology increases in prevalence in people's daily lives, the number of advanced applications are increasing in our vehicles. Technology has inherent risks and failures that are deemed unavoidable. Luxury vehicles typically incorporate more technology than non-luxury vehicles, but consumers believe that luxury brands are of higher quality than non-luxury brands. There appears to be a fundamental disconnect between the perceived quality of luxury vehicles and the failures associated with technologies incorporated in them. This study seeks to examine the effect of technology penetration on vehicle recalls and assess whether luxury status moderates this effect. To address the question, I use secondary data from Ward's Automotive on US-produced sedans from 2003-2011 and run panel regressions to test the hypotheses. My results show that technology options appear to have no impact on vehicle recalls, and that luxury status appears to moderate the relationship between recalls and technology options.

Key words: Technology, recall rates, luxury vehicles, quality

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Introduction

Oftentimes, purchasing a vehicle is the second-largest expenditure for a household. If a consumer is making such a purchase, he or she would want to ensure that the vehicle is of high quality and without defect. Consumers today have more resources than ever to learn about their prospective vehicles, and oftentimes these resources focus on technology or safety features. Few studies focus on expected reliability of such features. It is even more natural to understand why a luxury vehicle buyer would want to make sure his or her vehicle is of high quality and reliable. With a purchase price larger than a non-luxury vehicle, it is insufficient in a discerning buyer's mind for the luxury vehicle to have only higher quality materials—it must have higher operational quality as well.

One key point that dealerships use to woo buyers into purchasing vehicles is the advanced technology within them. One such example is shown in the 2014 Mercedes-Benz S-Class. It incorporates what the company calls "MAGIC BODY CONTROL;" this innovation uses a camera hidden within the vehicle's windshield to detect road imperfections, and the system "instantaneously adjusts the suspension to smooth out harsh road conditions" (Armstead, 2013).

It is worth pointing out, however, that technology and IT systems are inherently prone to failure. For instance, stability control software has proven troublesome for both Mercedes-Benz and Audi in the past (Williams, 2004). It stands to reason that the more sophisticated technologies that are placed into a vehicle, the higher risk that vehicle has for technological failure. Cars incorporating technology options are essentially complex systems with closely-linked subsystems. Normal Accidents Theory states that accidents are inevitable in systems that are complex and tightly-coupled. Most cars, by extension, could have Normal Accidents Theory applied to them (Rijpma, 1997). The potential safety consequences of an inevitably malfunctioning vehicle system are enormous—enough so that they could potentially cause fatal collisions.

In the automotive industries, catastrophic failures are typically handled in the form of recalls. The manufacturer can either perform an involuntary recall (forced by the NHTSA) or a voluntary recall (at its discretion). During this process, notifications are sent to vehicle owners informing them of the potential malfunction, and owners are invited to take their cars to a dealership or service location to be fixed with no charge. On average, this costs manufacturers $200 per vehicle (Jarrell & Peltzman, 1985). It is estimated that each vehicle recall may cost over $20 million (Shah, Ball, & Netessine, 2013). This process is tiresome for consumers, damaging to vehicle brands, and expensive for auto manufacturers.

Luxury buyers believe that luxury brands imply better quality than non-luxury goods (Wang, Sun, & Song, 2011). This can be applied in the same sense for new car buyers—they believe new cars are of higher quality and more luxurious than used cars. However, depending on the model, a used car may actually have fewer future recalls than its new alternative. The perceived quality of luxury and new goods is well-established, and these buyers likely assume that their vehicles have a higher quality than non-luxury or used vehicles.

The inclusion of advanced technology and the perceived quality of luxury vehicle seems to be conflicting. Studies have compared luxury vehicle recall rates on aggregate with non-luxury vehicle recall rates, but never before have these studies linked recalls to the factor of technology options.

I hope to fill the gap in this study by examining the effects of technology options on vehicle recall rates, and it also analyzes how luxury status may influence this relationship. Technology systems are prone to failures, and it is well-established that luxury vehicles today have more advanced technology than their non-luxury counterparts (Jayaraman, 2013; Partridge, 2011; Rijpma, 1997). Since it is difficult to categorize each vehicle on a scale based on the technologies it includes without subjective bias, this thesis will attempt to quantify the effect of technology by analyzing penetration of multiple technology options in vehicles; including navigation systems, stability control, and side airbags. These three options were chosen because they represent separate areas of vehicle technology: software (stability control), mechanical (side airbags), and experiential/non-critical (navigation systems). Technology option data are gathered from Ward's automotive for 2003-2011 US-produced sedans. I will test the effect of these on recalls as well as how luxury status moderates this relationship using a panel regression model.

Current research has focused on different realms of vehicle data. Studies have examined how plant-level data, component-level data, and the variety of components in cars influence quality and recalls (Bray, Serpa, & Colak, 2016; Shah et al., 2013). This study opens a new area of research, as it is the first to examine technology options' relationship with recalls.

The results of this study are intensely relevant to consumers and auto manufacturers. The results may upend the traditional assumption that newer and luxury cars are of higher quality, and consumers may demand that all vehicles become more reliable. This has happened in the past with chip manufacturers—high-quality Japanese chips flooded the market, and consumers demanded better quality from all manufacturers (Garvin, 1987). Higher technology quality could result in fewer recalls and potentially fewer consumer fatalities from failures. Vehicle brands may also take notice and look at ways to decrease recall rates by retooling their IT initiatives or by speeding up IT talent acquisition. Since recalls cost an estimated $20 million each, automakers surely would seek to minimize any negative effects their technologies have (Shah et al., 2013).

The rest of this study is organized as follows. Section two includes a literature review of consumer perceptions of luxury goods, the failure potential of technology, vehicle recall rates, and hypothesis development. In section three, I will describe my data collection and analysis methods. In section four, I will describe the main variables, the analysis method, and its appropriateness. In section five, I will report the main results of my method, and in section six I will discuss the implications of my findings, limitations, and implications for future research.

Literature Review and Hypotheses

2.0 Introduction

This literature review section is divided into three subsections, and the first section analyzes the inherent problems that accompany technological pursuits. The second section discusses the incidence of vehicle recalls over time, and the reasoning behind my first hypothesis. The final section shines light upon how current research supports the notion that luxury goods are perceived to be higher quality items, and the reasoning behind my second hypothesis. I intend to connect the problems of technology directly to vehicle recalls, and I will also examine how luxury status may moderate this relationship.

2.1 Failure of Technology

Technology presents the risk for dramatic failure. As automakers increase the technology components of their cars, they expose their customers and themselves to more risk (Kwiecinska, 2010). Although technological systems can work more efficiently, the specter of failure is nearly always present.

This is shown in Normal Accidents Theory, and the theory states that systems with increasing complexity and tight-coupling have increasing chances of failure (Rijpma, 1997). In the theory, complexity is likely in a system where components have many functions, where components are close to each other, and in systems that have some sort of reasoning and calculation (Rijpma, 1997). Tight-coupling is likely in a system with repeated and time-dependent processes, with inputs that cannot be substituted, where safety devices are included, and where improvising is impossible (Rijpma, 1997). These characteristics describe a typical vehicle's technology systems.

With technology, mistakes that would have been trivial in the past have now become fatal (Chiles, 2001). This is especially true with automotive systems. If a stability control system fails, a driver could potentially lose control of their car and crash, which happened to both Audi and Mercedes-Benz (Williams, 2004). Clearly the consequences of automotive technology failures can be fatal. Others agree with Normal Accidents Theory and Chiles's findings, and add that "hidden or apparently minor design errors" may surface in these systems as well (Dumas, 2002, p. 281). Dumas adds that, for the most crucial technologies that humans possess, the best way to solve issues is to learn from mistakes (2002, p. 281). For technologies that can create destruction, however, perfection is critical. Despite this, Chiles finds that perfection can only be truly attained when the system is off (2001). It has also been shown that complex vehicle components can have failure rates 4.9 times higher than typical, average components, and that same, albeit less strong, relationship holds for new components (Bray et al., 2016).

The problems rooted in technology are far deeper than hardware or software failure. These are created by humans, and they are a product of human nature. Partridge (2011) writes that "Nothing is easier, and more difficult to resist, than creating a program that is totally beyond the programmer's conceptual grasp" (p. 10). Mercedes-Benz's MAGIC BODY CONTROL seems precisely like a system that is too complex for a human to understand it (Armstead, 2013). Possibly due in part to this conceptual disconnect and the standard practice of having multiple coders contribute to a single project, Partridge finds that "conventional IT system construction is excessively fragile" (2011, p. 300). It should be noted that, though Normal Accidents Theory bodes poorly for technology systems, it has a counterpart in High Reliability Theory. High Reliability Theory involves using organizational strategies to deal with complex systems, and the Theory proves to be a counterweight to Chiles's arguments (Rijpma, 1997).

Vehicles today involve ample numbers of technology applications and software code, and assessing the role of technology failure in vehicles is an important area to examine (Jayaraman, 2013). This is especially important considering that current studies have focused on how the variety of components in cars, plant-level data, or even component-level data influence quality and recalls (Bray et al., 2016; Shah et al., 2013). This study is the first to examine technology options, and it seeks to determine the effect on recalls when technology options are applied in vehicles.

2.2 Vehicle Recalls

Vehicle recalls have been increasing in number as the number of vehicles on the road increases over time (Bates, Holweg, Lewis, and Oliver, 2007). This seems to be a natural conclusion. Because vehicle recalls have always occurred, when more vehicles are sold, more vehicles will be recalled. Bates et al. (2007) was able to find that the number of recall incidents have shown a two-to-threefold increase in quantity over 1992-2002. US data support these findings as well. In 1966, there were 58 recalls; in 2000, there were 631; in 2008, there were nearly 800 (Ahsan, 2013). Ahsan (2013) finds that "the number of automobile recalls in the US has increased sharply in the last two decades" (p. 5). However, while incidences of recalls are increasing, recalls per vehicle manufactured is not. In the UK, when recalls are normalized against vehicle registration data, there is no positive or negative correlation that can be found concerning recall rates over time (Bates, et al., 2007). This means that manufacturers are not getting better nor worse at preventing recalls—they are steady over time. This could be attributed to many things: higher quality being dragged down by higher volume, complexities of manufacturing at plants around the world, or recurring problems associated with the technological options in the vehicles. Interestingly, it is estimated that 60 to 70 percent of vehicle recalls in developed markets such as the US and Europe are due to software issues, and Audi and Mercedes-Benz have learned that software quality is necessary (Jayaraman, 2013; Williams, 2004). This study intends to quantify the effect of technology on vehicle recalls.

2.3 Hypothesis 1

Technology in vehicles has only been recently implemented, and "most innovation in the design of motor vehicles stems from the development of electronics" (Hines, 2013). Due to the rapid advances in technology in past decades, it is natural to assume that older vehicles do not widely use the technologies present in newer vehicles. Navigation systems, stability control systems, and even side airbags are options in today's new vehicles that had low adoption rates in the past. These features have increased in penetration over the last two decades, and it is intuitive to think that vehicles today incorporate significantly more technology options than vehicles in the past. I have sought to establish that with technology comes at a cost, and technology problems are now owners' top complaints about their cars. (Dumas, 2002; Jensen, 2016; Partridge, 2011). Therefore, I hypothesize:

Hypothesis 1: Technology option penetration is positively associated with recalls.

2.4 "Luxury" As a Quality Dimension

Luxury goods are premium products whose companies seek to differentiate them from typical non-luxury goods. The premium aspect with luxury goods also brings a higher price than regular goods. The psychology behind luxury consumers is often studied, and it has been shown that luxury is a subjective concept that depends entirely on context (Walley, Custance, Copley, & Perry, 2013). Walley et al. identified five main dimensions of a luxury consumer and found that luxury consumers typically have Affect, Characteristics, Status, Gifting, and Involvement dimensions (2013, p. 831). The Affect dimension had a strong association with the statement that "Luxury brands are of a higher quality than non luxury brands" (Walley et al. 2013, p. 829). This belief in the quality of luxury goods appears to hold despite cultural differences as well. Chinese consumers from overwhelmingly agreed in a study that luxury goods are, in general, better quality products (Wang, Sun, and Song 2011). Chinese consumers also agree in other statements that luxury goods are of higher quality, luxuries are worth the money, and luxuries are detail-oriented (Wang et al. 2011, p. 352). The belief in the quality of luxury goods appears to remain in China even though **"**Chinese luxury consumers are likely to focus more on external social needs than on internal individual needs" (Wang, et al. 2011, p. 348).

It is also noteworthy that two of Garvin's eight dimensions of quality are reliability and perceived quality (Garvin, 1987). Garvin notes that quality dimensions often interact with each other, and he notes that Honda initially chose to tell consumers that some Hondas were made in America; instead, they preferred consumers to perceive them as higher-quality, 100% Japanese cars (Garvin, 1987). This applies to luxury cars because, since their perceived quality is higher, consumers likely expect higher reliability as well. It is clear that past studies show that consumers believe that luxury goods are of higher quality, so it is likely that these beliefs hold for luxury vehicles.

Given the notion of higher quality, it is possible that luxury status buffers a vehicle from technology failure. However, Bray, Serpa, and Colak (2016), in their study of supply chain distance's effect on component failure rates, found that luxury vehicle components are 2.84 times more sensitive to supplier geographic distance. This may imply that luxury components have higher failure rates. For example, Audi and Mercedes-Benz proved victims of stability control software recalls in the late 1990s (Williams, 2004). Empirically, it is essential to evaluate the relationship between luxury status, technology, and recall rates.

2.5 Hypothesis 2

The inherent failures of technology and higher levels of technology in luxury vehicles imply that luxury vehicles will have more issues with technology, and, as a result, more recalls. Despite this assumption, luxury vehicles are viewed by consumers as possessing a higher level of quality (Galloway, 2010; Walley, Custance, Copley, & Perry, 2013; Wang et al., 2011). Literature regarding technological failures, such as Normal Accidents Theory, is more compelling than fickle consumer expectations of luxury cars. Therefore, I hypothesize:

> *Hypothesis 2: Luxury status moderates the relationship between technology option penetration and recalls.*

To summarize, technology problems are seemingly unavoidable, even when following best practices, due to human nature and the complexity of IT systems. Furthermore, while recalls per vehicle manufactured may not be increasing, the number of vehicles and incidences of vehicle recalls have been steadily increasing over time. Lastly, consumers view luxury goods as higher quality across cultures and personality types. Current research fails to combine these areas and discover the effect of technology in vehicles and its effect on recall rates and how luxury status moderates this relationship. Luxury vehicles, which are perceived to have the highest quality, also make extensive use of technology, which is associated with numerous problems. Luxury vehicles can have as many as 100 million lines of code while non-luxury vehicles have typically 20 to 30 million lines (Jayaraman, 2013).

Current studies have not focused on technology options in vehicles, and this study does (Bray et al., 2016; Shah et al., 2013). This research seeks to connect technology, luxury, and recalls and study the impact of technology options in vehicles and how that impact changes in luxury vehicle applications. Hypothesis 1 seeks to understand the effect of new technological options on vehicle recalls, and Hypothesis 2 seeks to see how the luxury dimension alters that relationship between the two variables.

Data and Methods

3.1 Data Sample

My dataset comes from a combination of Ward's Automotive, a leading automotive research company, and a past study done by Shah, Ball, & Netessine (2013). These data were used successfully in their study, and this study also slightly improves on their dataset. Shah, Ball, & Netessine used seven model years: 2000-2006 (2013). However, my study uses nine model years: 2003-2011. I used these model years to achieve the highest amount of technology option penetration possible while balancing the lack of recalls typically associated with extremely recent model years. I also expanded the dataset to provide more accuracy through more observations over time.

All recall data was accessed from the NHTSA website; these data are government-created and therefore a reliable source. I accessed vehicle recall data in November 2016 for the 2003-2011 model years. In the study, a vehicle model year averages 3.77 recalls over its lifetime and has a standard deviation of 3.4 recalls.

My dataset contains all US-manufactured sedans from model years 2003-2011. The data contain 10 manufacturers (Chrysler, Ford, General Motors, Honda, Hyundai, Mazda, Mitsubishi, Nissan, Toyota, and Volkswagen), and there are 83 different vehicle models. There are 409 model year observations.

I analyze my data at a model year level to account for differing levels of technology options for each model year. This structure also allows for specific model year recalls to be allocated back to the vehicle that created them. For instance, a manufacturer could have a recall related to a single vehicle's model year, and this study allows for that recall to be allocated to that vehicle's model year. The structure also allows for a more direct relationship between technology option penetration and the recalls associated with a vehicle.

3.2 Dependent Variable: Recall Count

The dependent variable used in my analysis is the count of recalls for a specific model in a given model year, which I call "recall count." For example, the 2006 Chrysler 300 has had 5 recalls over its lifetime. The recall count variable would be 5 for that model. All recalls, no matter when they occurred, are brought back to the vehicle model year they originated from. Out of 409 observations, 66 have a recall count of 0. This is noteworthy, as over 16% of vehicles had no recalls. The recall count data exhibit heavy skew and have many outliers. Because of this, in the study, recall count is maxed at a value of 7. This still accounts for 90% of all model years.

If recall count were not altered, the results of this study would be invalid. The model would be heavily skewed by the number of extreme outliers in the data. For example, only 18 out of the data's 409 model year observations have over 10 recalls, and one model year has 22 recalls. These outliers do not explain the vast majority of vehicle recalls and may skew the model, so I capped their recall count at a value of 7. In total, 44 model years are affected by this recall cap.

3.3 Independent Variables: Stability Control, Navigation Systems, Side Airbags

There are three independent variables in my study: stability control, navigation systems, and side airbags. This is unique to my study, and these three have not been used as proxies for technology before. These variables are again associated with a specific model in a given model year, and they are percentages to reflect the penetration of the option. I measure penetration because this best fits my hypotheses. If an automaker has higher penetration of an option instance, according to my first hypothesis, this should provide more opportunity for failure under Normal Accidents Theory and result in higher recalls. To further explain how penetration is measured, if 33.4% of 2004 Chrysler 300s had a navigation systems installed, the navigation systems variable for that model would be .334. I chose these three options from different technological areas to gain a more holistic view about how technology options affect a car's recall rate. Stability control is a software-based option, navigation systems are an experiential, non-critical technology, and side airbags are a more mechanical, design-related technology.

Stability control. This is a safety technology option that is integrated into a vehicle's software and controls vehicle braking responses when the vehicle loses traction. It is not currently required for US vehicles, but it was proposed as a requirement and was quickly made standard by many automakers (Valdes-Dapena, 2006). Stability control had nearly universal adoption by the end of our study's observed years. In the study, stability control has an average penetration rate of 34% and a standard deviation of 43.73%.

Navigation systems. This is far different from the other options. It is a luxurious, experiential technology option in a car. It had nearly zero adoption at the beginning of the study and amassed only small adoption rates by the end of the study; this is likely a reflection of its high expense and luxuriousness. In the study, navigation systems has an average penetration rate of 9.3% with a standard deviation of 19%.

Side airbags. Finally, I chose side airbags as an option to reflect a complex, mechanical technology in a car. Side airbags are a type of technology that has to be incorporated into a vehicle's design, so I felt this variable reflects a different aspect of vehicle technology. Adoption for side airbags was low at the beginning of our study and neared 100% at the end. In the study, side airbags has an average penetration rate of 61.9% with a standard deviation of 44.3%.

3.4 Control Variables: Years Since Launch, Manufacturer, Luxury, Model Year, Volume

I use five control variables in this study: years since launch, manufacturer, luxury, model year, and volume.

Years since launch. I incorporate this variable to account for the fact that a newer model may be more likely to experience a recall. This control variable is identical to that present in past studies, so the data were obtained from them (Shah et al., 2013).

Manufacturer. These dummy variables are created to account for systematic differences in recall rates across companies.

Luxury. A dummy luxury variable was created from Ward's data that classified vehicles as luxury or non-luxury. Examples of luxury vehicles according to Ward's are the Chrysler 300, Chevrolet Corvette, and Acura TL. Luxury vehicles are lower-volume and have a perceived higher quality, so this allows the study to control for any effects of luxury vehicles.

Model year. Dummy variables are used to account for the fact that recalls may vary by each year.

Volume. Finally, I used the natural logarithm on volume (ln volume) to account for scale when producing a specific vehicle model.

3.5 Exploratory Data Analysis

Figure 1 shows that the recall count variable has an extreme negative binomial distribution. The outliers on the graph are far from the median recall instances, and they are not representative of the true number of recalls per vehicle. 89.24% of all model years have 7 or fewer recalls; therefore, I created an adjusted recall count variable that caps recall instances per model year at 7. This prevents the data from being skewed by the larger number of 10 recall instances. This adjustment of the dependent variable allows for regression models to more accurately fit the data, and it decreases the need for a negative binomial model.

Recall incidents per year can be found in Figure 2. The distribution is fairly constant, and it interestingly shows a decrease in total vehicles affected by recalls as time passes. This differs from recent studies, but it is likely due to the fact that this dataset is limited only to US-produced sedans. It is noteworthy that recalls would be so stable over such a long time period, and it may suggest that automakers continue to struggle with the dependability of new models.

All three key independent variables of interest show increasing adoption over time. Stability control shows the sharpest rate of adoption, and side airbags show the steadiest rate of adoption and end in 2011 at nearly 100% adoption. Navigation systems are non-safety-related and largely experiential: their adoption rate increases over time but never reaches 20% of new cars. The graphs of technology variable adoption over time as well as adoption for luxury cars can be seen in Figure 3.

Table 4 shows all variables and basic statistics such as mean, maximum, and standard deviation. It is worthwhile to note that, since the independent variables reflect technology complexity, that they are highly correlated with each other. A correlation matrix of all variables can be found in Table 5.

3.6 Empirical Approach

I run a panel regression to test my first hypothesis with the dependent variable recall count. Hypothesis 1 is supported if the p-value of any of my independent variables is under .05. For my second hypothesis, I run a panel regression with three interaction terms, and the terms are stability control*luxury, navigation systems*luxury, and side airbag*luxury. Hypothesis 2 is supported if the p-value of any interaction term is under .05.

A panel regression is a simple regression model that follows a group of individuals over time. Panel regressions are ideal for longitudinal datasets that provide observations from a group of individuals over time, and panel regressions are often used on economic-related data like that of employment and income studies (Hsiao, 2004). When data are structured in a panel, it is natural to use a panel regression to evaluate them. The two major types of panel regression are fixed effects or random effects regressions, and fixed effects regressions are used when trying to control for an individual's effect on the outcome variable. A random effects model assumes variation across individuals is uncorrelated and random. A fixed effects regression may be better used when some variable, say manufacturer skill, is assumed to consistently affect results and needs to be controlled. A random effects model is better for when it is assumed that variations across individuals are not correlated with the independent variable used in the model. A random effects model also allows results to be generalized to a larger population. Panel data are not ideal for using on data that are serially correlated, as the presence of serial correlation may create statistical significance where there is none.

A panel regression is used because it identifies that, for instance, a 2002 Chrysler 300 and a 2003 Chrysler 300 are inherently related, and it prevents these relationships from confounding the regression. Instead, the panel regression will search across models and look for relationships between different models over time. This panel regression also is a random effects model, which means that it assumes individuals that have unique attributes are the result of random variation.

Panel regressions are strong with panel data and when using random effects or fixed effects models. However, panels struggle with heteroskedasticity and serial correlation in data, and other models may be better used with panels that exhibit these characteristics. For my study, the random effects panel model I use fits the data well, and, since there is no cross-sectional dependence, heteroskedasticity is not a concern. However, it should be noted that my data are serially correlated, and the panel regression model does not account for this.

I also consider several alternative methods to a panel regression. They are a negative binomial panel regression, a panel regression with Driscoll-Kraay standard errors, and a generalized estimating equation (GEE) panel regression as used by Shah, Ball, and Netessine in their automotive study (2013). I choose not to use the negative binomial regression because I manually alter the dependent variable to negate its negative binomial distribution. The Driscoll-Kraay panel that accounts for serial correlation is a promising model, and its results are similar to the panel regression's results. I chose to report results from the panel regression because it is a simpler model. Finally, I do not use a GEE panel for the same reason: the results are similar enough to the simple panel regression that there seems to be little value in using a more complex model.

Results

4.1 Regression Results

Table 6 shows my main regression results in the panel regression column and several control variables are significant. The year 2008 has a coefficient that is strongly negative at -0.78 (p-value .04). Next, years since launch's coefficient is a mild -0.02 (p-value .07). Finally, volume's coefficient is 0.40 (p-value .001).

The beta for the regression is 0.91 with a standard error of 2.36. When all independent variables are tested in tandem, navigation system adoption is the only significant variable. and it has a strongly negative coefficient of -2.33 (p-value .01). These results directly contradict hypothesis 1b and provides no support for hypotheses 1a and 1c. Interestingly, stability control has a coefficient of 0.65 (p-value .06), which is the opposite of navigation systems. This may suggest that peripheral technologies relate to fewer recalls and software-based technologies may relate to more recalls.

4.2 Interaction Regression Results

Table 7 shows my results for hypothesis 2, and Figure 8 contains graphs of the variable interactions. Control variable coefficients change slightly in this model, but all stay at the same level of significance. When tested, the luxury*stability control has a coefficient of -1.05 (p-value .04), and the luxury*side airbag has a coefficient of -1.72 (p-value .004). Luxury*navigation systems is insignificant and has a coefficient of -2.00 (p-value .28). Because two out of three terms are significant, this provides some support for hypothesis 2. In two cases, the luxury dimension changes the effects of technology on recalls in a negative way. All three interaction terms have a negative coefficient, and two of these cases are significant.

4.3 Robustness Checks

I conducted four robustness checks on hypothesis 1 to evaluate my panel regression's performance. All robustness checks can be found in Table 9.

I chose to use another panel regression equipped with Driscoll-Kraay standard errors (xtscc function in Stata). Through use of Driscoll-Kraay standard errors, this model robustly accounts for serial correlation by using standard errors that allow for more than first-order autocorrelation between results. All results remain the same as with the panel regression; however, coefficients and results become more significant. The beta of this model is -3.22 and is significant (p-value .05). The standard error of the model is 1.62. The years 2003, 2004, 2005, 2006, and 2011 now hold the highest significance (p-values .000), and their coefficients are -

2.45, 0.31, 0.51, 0.37, and 2.11, respectively. Another area of note is the automaker control variables. Ford is insignificant with a coefficient of -1.86 (p-value .052), Mazda is significant with a coefficient of 2.11 (p-value .02), Volkswagen has a coefficient of -1.56 (p-value .04), and Mitsubishi is insignificant with a coefficient of -1.53 (p-value .07). Furthermore, the luxury dimension is now significant and a has coefficient of 0.72 (p-value .02), which points to higher recalls among luxury cars. This may be because serial correlation in the data are masking significant results, and the Driscoll-Kraay model adequately accounts for them. Though this model's results have lower p-values and stronger coefficients than the original, none of its results conflict with the simple panel. Therefore, this model largely confirms the results provided by the panel regression.

My second check is a simple first-order autocorrelation panel regression (xtregar function in Stata). Since this model only accounts for first-order autocorrelation, it accounts for it less robustly than the Driscoll-Kraay model. This model has a constant of 1.12 and a standard error of 2.20. Differences in results when compared to the panel regression are minimal. Navigation systems still is significant (p-value .01), and its coefficient strengthens to -2.35. The same happens for the year 2008 (p-value .04), and its coefficient changes to -0.82. The year 2009 changes from the original panel, and now has a stronger coefficient of -0.76 (p-value .08). Interestingly, the stability control variable becomes insignificant and its coefficient changes to 0.50 (p-value .14). Finally, volume's coefficient stays the same at 0.40 (p-value .001). These results coupled with the Driscoll-Kraay panel are telling, as this model seems to occupy the middle ground between the original panel and the Driscoll-Kraay panel. Perhaps this may reflect that autocorrelation in the data may be obscuring actual relationships.

Because the recall count variable has a subtle, residual negative binomial distribution even after adjusting for recall count, I also choose to use a negative binomial panel regression to examine it. This model has a constant of 15.93 and a standard error of 274.43, so its results may be flawed. Despite this, it is noteworthy that navigation systems is more significant and has a coefficient of -1.25 (p-value .004). Stability control maintains its significance and its coefficient changes to 0.24 (p-value .07). The year 2008 loses significance, and its coefficient changes to -0.20 (p-value .16). Finally, volume's coefficient becomes 0.16 (p-value .003). Interestingly, the model seems only to drive coefficients closer to zero. This could be due to the fact that I have altered the recall count variable, or it could reflect that there are simply fewer recalls in later years of the study.

Finally, as Shah, Ball, and Netessine (2013) have done, I use a Generalized Estimating Equation. GEE allows the dependent variable to be randomly distributed, and it also allows for the dependent variable to be clustered. This is somewhat helpful for my data, as recall counts are slightly clustered near lower recall counts. Shah, Ball, and Netessine also note that the GEE equation has been used to great success in past research when dependent variables often equal zero (2013). It has also been used successfully in multiple past studies (Rhee & Haunschild, 2006; Shah et al., 2013; Sine, Shane, & Gregorio, 2003; Wowak, Mannor, & Wowak, 2015). The GEE model largely confirms the results of my simple panel regression, and it has a constant of 0.25 with a standard error of 2.11. Stability control maintains its significance, and its constant changes slightly to 0.64 (p-value .07). Navigation systems' constant changes to -2.39 (p-value .008). Interestingly, the year 2008 loses significance, and its coefficient moves toward zero and becomes -0.67 (p-value .08). Finally, volume's coefficient gets stronger and becomes 0.45 (p-value .000).

Discussion

The results show mixed support for my assertion that stability control, navigation systems, and side airbags increase recalls and that luxury status moderates this relationship.

However, three important findings emerged. First, despite the negative relationship between navigation systems and recalls, there is inconsistent evidence that technology options on aggregate are associated with positive or negative recalls. Secondly, it appears that technology applications in luxury vehicles are associated with a reduction in recalls. Luxury status appears to mask the bifurcated relationship between technology and recalls in luxury and non-luxury cars for stability control and side airbags. Finally, contrary to popular beliefs about quality, it appears that luxury vehicles do not have significantly fewer recalls than non-luxury vehicles. In this section, I will expand upon my findings for technology and recalls, and, next, I will discuss the implications of luxury's moderation of this relationship. Finally, I will discuss the surprising absence of a significant relationship between luxury status and recalls.

5.1 Technology and Recalls

The data do not show particularly compelling evidence for the assertion that aggregate technology options positively affect recalls. Stability control and side airbags are not statistically significant, and navigation systems is significant in a negative way. The negative effects of navigation systems directly contradict my hypothesis that navigation systems would be related to an increase in recalls.

However, navigation systems and stability control remain areas of interest. I classified navigation systems as a peripheral technology, and the option showed a strong negative correlation with recalls. Since it can be argued that cars with expensive, experiential navigation systems typically have other options installed, perhaps this may indicate that more highly optioned vehicles have lower recall rates. These lower recall rates could potentially be from more time being spent in assembly or design to account for the complexity of the options. This same effect was confirmed in the test of luxury's moderation of the relationship between technology and recalls, and stability control and side airbags in luxury cars predicted fewer recalls. The same results did not hold for navigation systems, which may be a reflection that the navigation systems option has a stronger aggregate association with negative recalls than an association on the more granular, class level.

Conversely, stability control is not significant in the main regression but has a p-value under .10, and it has a positive correlation with recalls. Stability control is a complex, software-based option. Although a software option was not significant in this study, it may be worth examining in future studies the effect of software technologies on vehicle recall rates—especially considering that automakers have been proven to struggle with them (Williams, 2004). Stability control's results may be explained by the rapid adoption of the technology over the sample. As automakers implemented the system when it was rumored to be mandated, they may have been rushed. This could have led to more errors and the results shown in the data.

5.2 Luxury's Moderation of Technology and Recalls

It is noteworthy that stability control in non-luxury vehicles positively relates to recalls, as it is a software-based option and possibly has more opportunity for failure due to its complexity.

Interestingly, the luxury dimension is shown to be negatively related to recalls for vehicles equipped with stability control and side airbags but not navigation systems. The interaction term results are significant, whereas the panel results are not. This may indicate that technologies in luxury vehicles decrease recalls, which fits consumer perceptions of luxury vehicles.

Luxury vehicles tend to introduce new technologies and contain up to five times the amount of software code, so the results are surprising (Jayaraman, 2013). This seems to directly contradict the Normal Accidents Theory and favor High Reliability Theory (Rijpma, 1997). It is highly plausible that theory that luxury vehicle manufacturers follow the core tenets of High Reliability Theory, which are using redundancy, decentralizing decision making, and using multiple theories and processes at the same time to manage technology options (Rijpma, 1997). This may lead luxury vehicle manufacturers to place more emphasis on luxury vehicle technology applications and relate to a subsequent decrease in recalls. This would support what the data show.

Another area of note is navigation systems. As it was argued previously, cars with navigation systems likely cost more and have more complexity. This may point to an underlying variable, such as option density or even the MSRP of the car, that accounts for this relationship. It may be that vehicles that have more options and/or cost more have more effort put into their manufacture and have lower recalls as a result.

Finally, it is unexpected that stability control differs so markedly when applied in luxury vehicles versus non-luxury vehicles. Perhaps this is again a reflection of High Reliability Theory and the extra effort put into luxury vehicles. Stability control is the only option to show such a strong difference between vehicle classes, and it may allude to the instability of software. Since software issues represent 60 to 70 percent of vehicle recalls in major automotive markets, it is plausible that software applications in non-luxury vehicles are more unstable because due diligence was not performed to the same standard as in the luxury application (Jayaraman, 2013).

5.3 Luxury Status and Recalls

Only one model shows luxury status to have a significant relationship with recalls—the Driscoll-Kraay robustness check. Interestingly, the Driscoll-Kraay model found luxury status positively associated with recalls. I have posited that this model may best expose the underlying relationships due to its accounting for autocorrelation, and it is highly surprising that it would unveil a positive relationship between luxury and recalls. However, all other models find that luxury status has no significant relationship with recalls; therefore, it is unlikely that a significant relationship exists. This in itself is surprising—especially given the fact that technology options in luxury cars predict fewer recalls.

Given that consumers expect luxury vehicles to be higher quality, it is interesting to find that luxury vehicles have no significant results with recalls. This could be because there are multitudes of factors affecting luxury, and they confound each other and prevent any clear relationship between luxury status and recalls to emerge. It also could be a reflection of the inherent difficulties automakers face when producing vehicles. It is as if Normal Accidents Theory is true for luxury automakers on an aggregate level. Despite their successes at managing issues like the effects of technology options on recalls, it is likely far more challenging to manage the quality of an entire vehicle, and the results exemplify this.

Conclusion

This study makes multiple contributions to current academic literature, and it is of great value to the automotive industry and consumers. To my knowledge, this study is the first to examine the effect of technology options on recall rates, which is a completely new area of study. Furthermore, the results of this study may sway buyer behavior and change manufacturer behaviors with technology. Insights from the study could also prevent future fatalities related to vehicle technologies. This thesis has answered what effect technology has on recall rates and how luxury status influences this relationship.

6.1 Limitations of Study

The study does present several limitations, with the largest being the use of only three technology options to predict recalls. Technologies in cars can vary from mechanical (suspension) to software-based (blind-spot warning systems) to peripheral (navigation systems). It is clear that there are hundreds, if not thousands, of technologies that this study does not examine. An ideal situation would be the creation of a new variable that fully measures the technological capability of a car. A standardized "technology index" would be made for each vehicle, and recalls would be predicted from that. Unfortunately, this was beyond the scope of my current project though it leaves promising potential for future research.

Another limitation is the sample itself: US-manufactured sedans from 2003-2011 is a large sample but far from representative of all US vehicles. This limitation was created by differences in data reporting between the SUV, sedan, and imported vehicle segments. Since this study is lacking a true random sample, the results from the panel regression may not hold true across the entire population (Woodridge, 2010). This could possibly explain some conflicting results of the data.

The final notable limitation is the autocorrelation present within the data. Ideally, the data would have no autocorrelation, but it is inherent when measuring technology options over time. To account for this, I used two autocorrelation panel robustness checks, and the results from those models largely confirmed my results. Therefore, I believe this limitation has been satisfactorily addressed.

6.2 Implications for Future Research

This study has its limitations, but it provides opportunities and a solid foundation from which future research may continue. First, it has provided preliminary insight into technology option variables, and it has highlighted a need for a standardized technology index. Such an index would allow for a much more robust measure of technology's effect on recalls. Secondly, it has shown the necessity for further control variables. Some results of this study are conflicting, and it is likely that some other factors are affecting recall rates. Manufacturing data such as location of vehicle manufacture, number of vehicles per manufacturing line, and number of lines used per vehicle are all absent from my study—these could have a large effect in future research. Furthermore, as previously noted, the sample in this study was confined to a small subset of all vehicles. Perhaps future research could use a sample across developed countries and all vehicle body styles.

As technology and vehicles continue to increase in frequency, researching their effects on vehicle recalls is crucial. This study, despite its limitations, has contributed to academic literature by analyzing technology options as a new area of study, and it provides a framework for future research on technology applications in vehicles.

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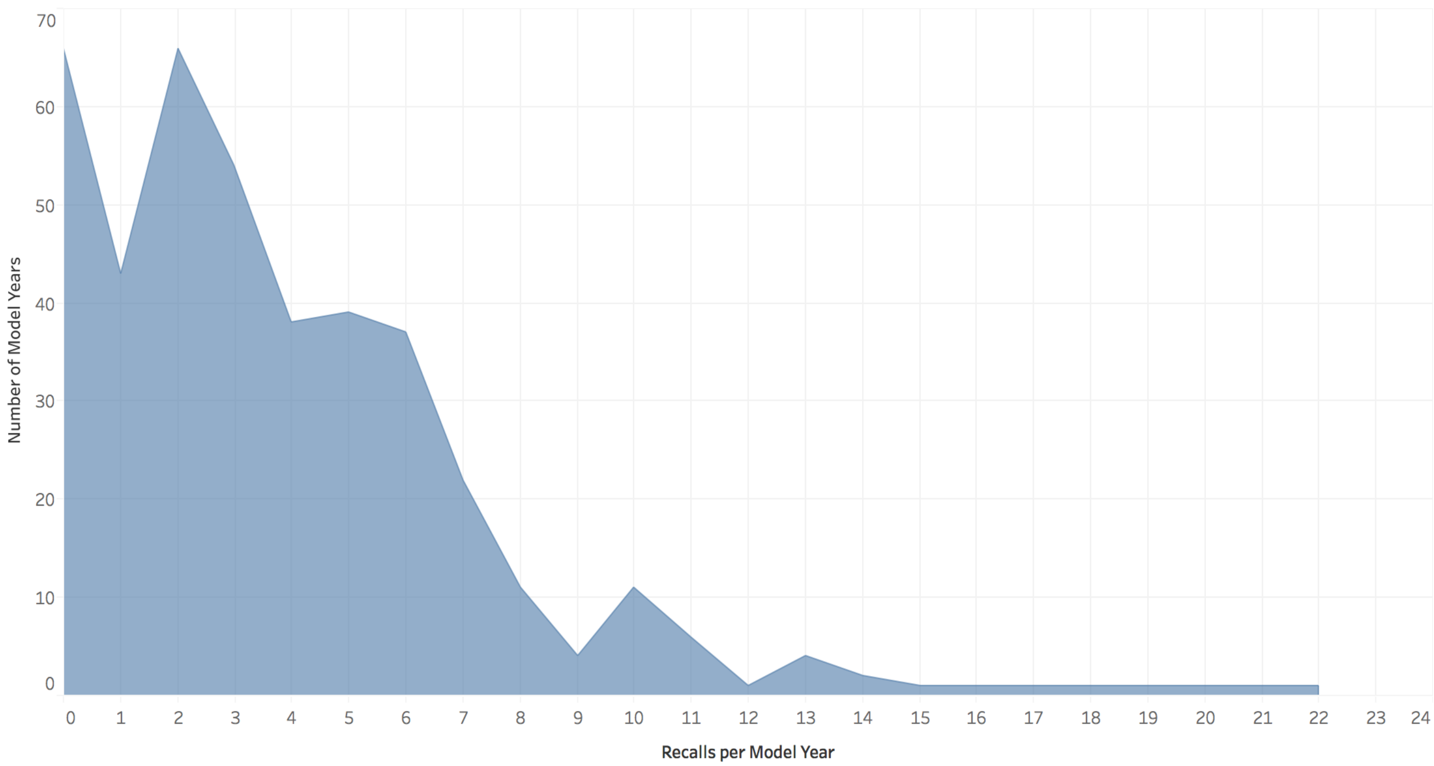
Figure 1: Recall Count Frequency Distribution



The plot of count of Recallcount for Recallcount.

Figure 2: Recalls by Year and Manufacturer

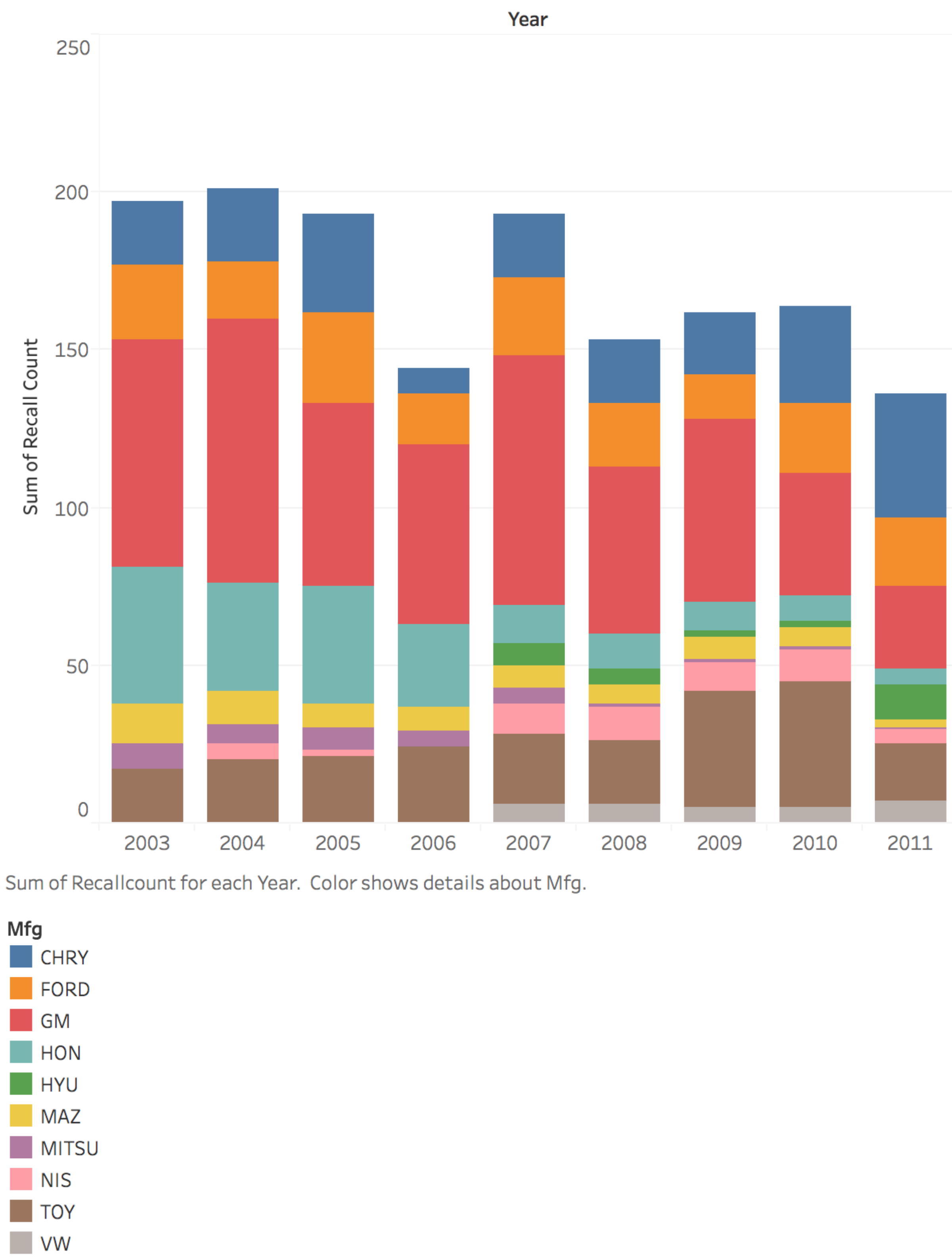


Figure 3: Option Adoption by Year and Luxury Status (0 is non-luxury, 1 is luxury)

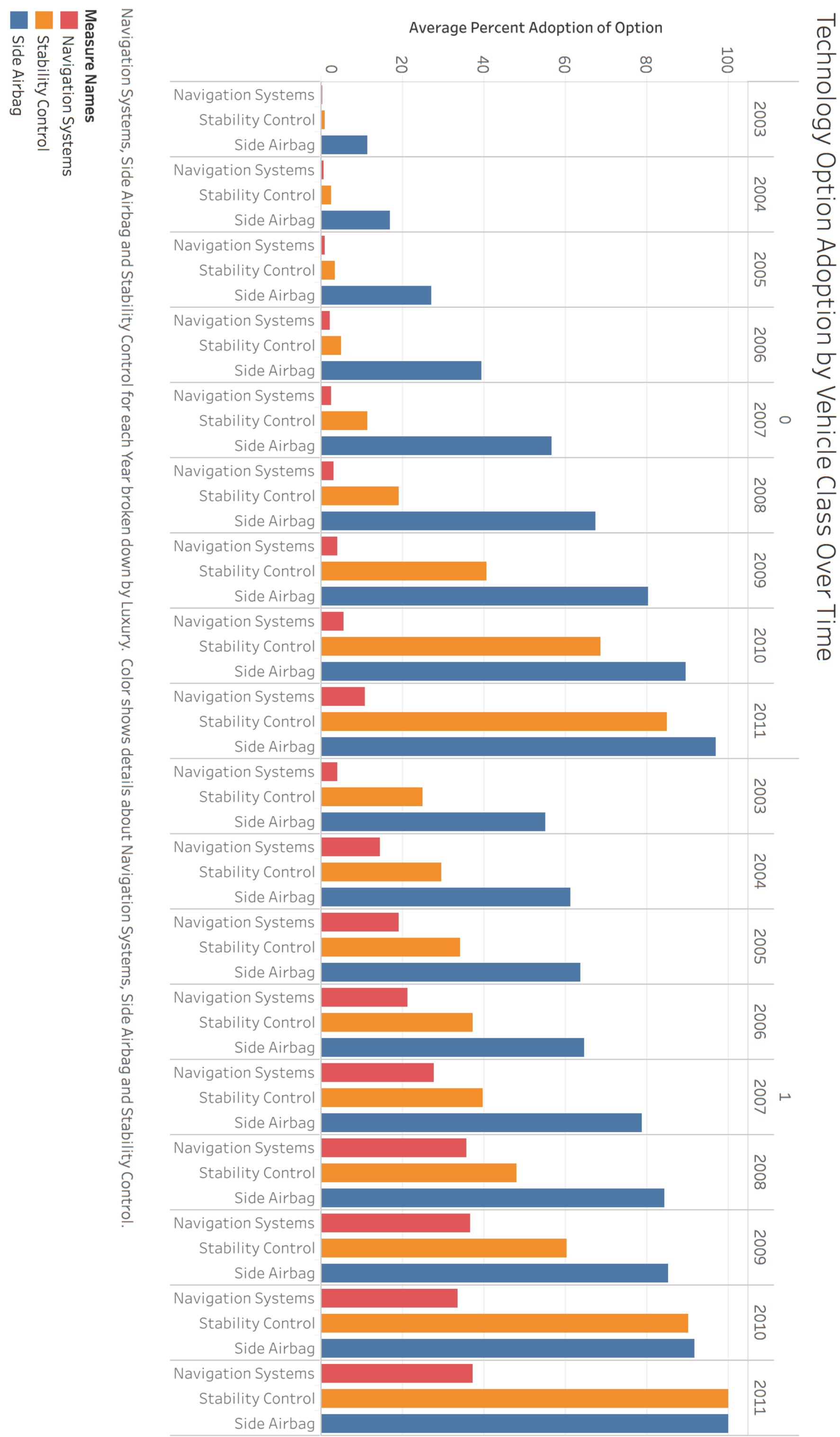


Table 4: Description of Variables and Summary Statistics

Variable	Description	Minimum	Maximum	Mean	Standard Deviation
Recalls	Number of product recalls per model per year	0	22	3.77	3.40
Stability Control	Percent of vehicles equipped with stability control	0	1	0.34	0.44
Navigation Systems	Percent of vehicles equipped with navigation system	0	1	0.09	0.19
Side Airbags	Percent of vehicles equipped with side airbags	0	1	0.62	0.44
Years Since Launch	Number of years since original model launch year	0	58	17.04	15.63
Volume	Number of cars sold in model-year	19	485,370	103,796	101,979
Luxury	Luxury status	0	1	0.27	0.44
GM	Manufactured by GM	0	1	0.35	0.48
Toyota	Manufactured by Toyota	0	1	0.10	0.30
Honda	Manufactured by Honda	0	1	0.07	0.25
Ford	Manufactured by Ford	0	1	0.21	0.41
Chrysler	Manufactured by Chrysler	0	1	0.12	0.33
Nissan	Manufactured by Nissan	0	1	0.05	0.23
Mazda	Manufactured by Mazda	0	1	0.02	0.15
Volkswagen	Manufactured by Volkswagen	0	1	0.02	0.15
Mitsubishi	Manufactured by Mitsubishi	0	1	0.04	0.21
Hyundai	Manufactured by Hyundai	0	1	0.01	0.11
2003	2003 model-year	0	1	0.11	0.31
2004	2004 model-year	0	1	0.11	0.31
2005	2005 model-year	0	1	0.11	0.31
2006	2006 model-year	0	1	0.08	0.28
2007	2007 model-year	0	1	0.13	0.33
2008	2008 model-year	0	1	0.12	0.33
2009	2009 model-year	0	1	0.13	0.33
2010	2010 model-year	0	1	0.12	0.32
2011	2011 model-year	0	1	0.11	0.31

Table 5: Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1 Recall Count	1																	
2 Stability Control	-0.07	1.00																
3 Navigation Systems	-0.25	0.51	1.00															
4 Side Airbags	-0.15	0.52	0.34	1.00														
5 Years Since Launch	-0.04	-0.16	-0.15	-0.02	1.00													
6 Luxury	-0.19	0.23	0.51	0.19	0.07	1.00												
7 GM	-0.01	0.03	0.14	-0.18	-0.03	0.11	1.00											
8 Toyota	0.17	0.03	-0.07	0.03	0.03	-0.20	-0.25	1.00										
9 Honda	0.11	0.06	0.13	0.15	0.15	0.04	-0.20	-0.09	1.00									
10 Ford	-0.24	-0.12	-0.11	0.02	0.05	0.14	-0.38	-0.17	-0.14	1.00								
11 Chrysler	0.12	-0.02	0.03	-0.15	-0.24	-0.04	-0.27	-0.12	-0.10	-0.19	1.00							
12 Nissan	-0.10	-0.05	-0.03	0.16	0.01	-0.14	-0.18	-0.08	-0.06	-0.12	-0.09	1.00						
13 Mazda	0.19	0.01	-0.06	0.01	-0.12	-0.09	-0.11	-0.05	-0.04	-0.08	-0.06	-0.04	1.00					
14 Volkswagen	-0.01	0.17	-0.06	0.09	0.05	-0.09	-0.11	-0.05	-0.04	-0.08	-0.06	-0.04	-0.02	1.00				
15 Mitsubishi	-0.13	-0.05	-0.08	0.08	0.15	0.11	-0.16	-0.07	-0.06	-0.11	-0.08	-0.05	-0.03	-0.03	1.00			
16 Hyundai	0.06	0.12	-0.02	0.10	0.05	-0.07	-0.08	-0.04	-0.03	-0.06	-0.04	-0.03	-0.02	-0.02	-0.02	1.00		
17 2003	-0.08	0.43	0.14	0.28	0.02	-0.01	-0.05	0.02	0.01	-0.02	0.02	0.06	0.00	0.00	0.00	0.03	1.00	
18 2004	0.06	-0.19	-0.09	-0.25	0.08	0.01	0.06	-0.01	0.01	0.00	-0.03	-0.05	0.00	-0.05	0.00	-0.04	-0.12	1.00
19 2005	0.07	-0.17	-0.05	-0.18	0.04	0.04	0.02	-0.01	0.00	0.04	-0.01	-0.05	0.00	-0.05	0.00	-0.04	-0.12	-0.12
20 2006	0.05	-0.12	-0.01	-0.09	0.02	0.06	0.02	0.02	0.03	0.04	-0.06	-0.07	0.02	-0.05	0.02	-0.03	-0.10	-0.10
21 2007	0.03	-0.14	-0.02	0.00	-0.04	-0.03	0.01	-0.01	-0.01	0.00	-0.05	0.04	-0.01	0.04	-0.01	0.02	-0.13	-0.13
22 2008	-0.08	-0.07	0.03	0.08	-0.05	-0.03	-0.01	0.00	-0.01	-0.01	0.00	0.04	-0.01	0.04	-0.01	0.03	-0.13	-0.13
23 2009	-0.08	0.10	0.05	0.17	-0.06	-0.02	-0.04	-0.01	-0.01	0.00	0.02	0.04	-0.01	0.04	-0.01	0.02	-0.13	-0.13
24 2010	-0.03	0.33	0.06	0.23	-0.01	-0.02	-0.06	0.00	-0.01	-0.02	0.05	0.05	0.00	0.05	0.00	0.03	-0.12	-0.12
25 2011	-0.07	0.43	0.15	0.28	0.01	-0.01	-0.06	0.02	0.00	-0.02	0.04	0.06	0.00	0.00	0.00	0.03	0.99	-0.12
26 Volume	0.41	-0.24	-0.46	-0.14	0.23	-0.44	-0.15	0.17	0.22	-0.05	-0.06	0.09	0.00	0.11	-0.18	0.08	-0.07	0.06

	19	20	21	22	23	24	25	26
19 2005	1							
20 2006	-0.10	1.00						
21 2007	-0.13	-0.11	1.00					
22 2008	-0.13	-0.11	-0.14	1.00				
23 2009	-0.13	-0.11	-0.15	-0.14	1.00			
24 2010	-0.13	-0.11	-0.14	-0.14	-0.14	1.00		
25 2011	-0.12	-0.10	-0.13	-0.13	-0.13	-0.13	1.00	
26 Volume	0.03	0.06	0.05	0.03	-0.14	-0.10	-0.07	1.00

Table 6: Panel Regression Results—Recall Count

	1	2	3	4	5
Stability Control		0.45			0.65+
		(0.34)			(0.34)
Navigation System			-2.00*		-2.33*
			(0.92)		(0.94)
Side Airbag				-0.26	-0.27
				(0.32)	(0.31)
Volume	0.45***	0.43***	0.43***	0.45***	0.40**
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
Years Since Launch	-0.02+	-0.02	-0.03*	-0.02+	-0.02+
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
2003	-2.74	-2.71	-3.05	-2.81	-3.14
	(2.28)	(2.28)	(2.27)	(2.29)	(2.28)
2004	0.14	0.12	0.18	0.15	0.18
	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)
2005	0.20	0.17	0.27	0.24	0.27
	(0.34)	(0.34)	(0.34)	(0.34)	(0.34)
2006	-0.17	-0.21	-0.08	-0.11	-0.07
	(0.37)	(0.37)	(0.37)	(0.38)	(0.37)
2007	-0.40	-0.44	-0.28	-0.30	-0.22
	(0.34)	(0.34)	(0.34)	(0.36)	(0.36)
2008	-0.98**	-1.06**	-0.82*	-0.85*	-0.78*
	(0.34)	(0.35)	(0.35)	(0.38)	(0.38)
2009	-0.78*	-0.95*	-0.61+	-0.63	-0.68
	(0.36)	(0.38)	(0.37)	(0.41)	(0.42)
2010	-0.54	-0.86*	-0.34	-0.37	-0.59
	(0.37)	(0.44)	(0.38)	(0.42)	(0.48)
2011	1.83	1.44	2.42	2.08	2.20
	(2.28)	(2.30)	(2.28)	(2.30)	(2.32)
Luxury	-0.27	-0.41	0.13	-0.19	0.08
	(0.51)	(0.52)	(0.54)	(0.52)	(0.56)
Chrysler	-1.32	-1.07	-1.37	-1.43	-1.13
	(1.85)	(1.86)	(1.83)	(1.86)	(1.87)
Ford	-2.18	-2.00	-2.31	-2.26	-2.15
	(1.83)	(1.84)	(1.81)	(1.84)	(1.84)
GM	-1.61	-1.47	-1.59	-1.69	-1.49
	(1.80)	(1.81)	(1.79)	(1.82)	(1.82)
Honda	-0.51	-0.38	-0.31	-0.52	-0.10
	(2.02)	(2.04)	(2.01)	(2.04)	(2.04)
Mazda	1.42	1.56	1.32	1.38	1.47
	(2.46)	(2.48)	(2.44)	(2.48)	(2.48)
Mitsubishi	-1.89	-1.70	-2.13	-1.93	-1.92
	(2.16)	(2.17)	(2.14)	(2.17)	(2.17)
Nissan	-2.28	-2.04	-2.28	-2.29	-1.93
	(1.97)	(1.99)	(1.95)	(1.98)	(1.98)
Toyota	-0.69	-0.59	-0.68	-0.73	-0.56
	(1.90)	(1.92)	(1.89)	(1.92)	(1.91)
Volkswagen	-1.53	-1.57	-1.60	-1.56	-1.71
	(2.16)	(2.17)	(2.14)	(2.18)	(2.17)
Constant	0.49	0.49	0.79	0.56	0.91
	(2.35)	(2.36)	(2.34)	(2.36)	(2.36)
Model-years	409	409	409	409	409
Wald Chi²	77.14	78.85	82.73	77.54	86.70

Standard errors in parentheses, + p<.10, * p<.05, **p<01, ***p<.001
NOTE: Hyundai is omitted, as it is the reference category

Table 7: Moderation Panel Regression Results—Recall Count

	1	2	3	4	5	6
Stability Control	0.45	0.81*				
	(0.34)	(0.38)				
Luxury*Stability Control		-1.05*				
		(0.50)				
Navigation Systems			-2.00*	-0.54		
			(0.92)	(1.63)		
Luxury*Navigation				-2.00		
				(1.84)		
Side Airbag					-0.26	0.10
					(0.32)	(0.34)
Luxury*Side Airbag						-1.72**
	(0.34)	(0.38)				
Luxury	-0.41	0.01	0.13	0.32	-0.19	1.00
	(0.52)	(0.56)	(0.54)	(0.56)	(0.52)	(0.67)
Volume	0.43***	0.42***	0.43***	0.43***	0.45***	0.46***
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
Years Since Launch	-0.02	-0.02	-0.03*	-0.03*	-0.02+	-0.03+
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
2003	-2.71	-2.57	-3.05	-2.71	-2.81	-2.73
	(2.28)	(2.27)	(2.27)	(2.28)	(2.29)	(2.28)
2004	0.12	0.13	0.18	0.19	0.15	0.15
	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)
2005	0.17	0.17	0.27	0.28	0.24	0.25
	(0.34)	(0.34)	(0.34)	(0.34)	(0.34)	(0.34)
2006	-0.21	-0.22	-0.08	-0.08	-0.11	-0.13
	(0.37)	(0.37)	(0.37)	(0.37)	(0.38)	(0.37)
2007	-0.44	-0.43	-0.28	-0.27	-0.30	-0.30
	(0.34)	(0.34)	(0.34)	(0.34)	(0.36)	(0.36)
2008	-1.06**	-1.06**	-0.82*	-0.81*	-0.85*	-0.86*
	(0.35)	(0.35)	(0.35)	(0.35)	(0.38)	(0.37)
2009	-0.95*	-0.99**	-0.61+	-0.60+	-0.63	-0.66
	(0.38)	(0.38)	(0.37)	(0.37)	(0.41)	(0.40)
2010	-0.86*	-0.91*	-0.34	-0.35	-0.37	-0.38
	(0.44)	(0.44)	(0.38)	(0.38)	(0.42)	(0.42)
2011	1.44	1.22	2.42	2.05	2.08	2.00
	(2.30)	(2.29)	(2.28)	(2.29)	(2.30)	(2.29)
Chrysler	-1.07	-0.89	-1.37	-1.34	-1.43	-1.40
	(1.86)	(1.85)	(1.83)	(1.82)	(1.86)	(1.86)
Ford	-2.00	-1.86	-2.31	-2.31	-2.26	-2.12
	(1.84)	(1.83)	(1.81)	(1.80)	(1.84)	(1.84)
GM	-1.47	-1.29	-1.59	-1.56	-1.69	-1.45
	(1.81)	(1.80)	(1.79)	(1.78)	(1.82)	(1.82)
Honda	-0.38	-0.09	-0.31	-0.26	-0.52	-0.29
	(2.04)	(2.02)	(2.01)	(2.00)	(2.04)	(2.03)
Mazda	1.56	1.69	1.32	1.36	1.38	1.46
	(2.48)	(2.45)	(2.44)	(2.43)	(2.48)	(2.47)
Mitsubishi	-1.70	-1.60	-2.13	-2.17	-1.93	-1.77
	(2.17)	(2.15)	(2.14)	(2.13)	(2.17)	(2.17)
Nissan	-2.04	-1.85	-2.28	-2.30	-2.29	-2.28
	(1.99)	(1.97)	(1.95)	(1.94)	(1.98)	(1.98)
Toyota	-0.59	-0.48	-0.68	-0.69	-0.73	-0.65
	(1.92)	(1.90)	(1.89)	(1.88)	(1.92)	(1.91)
Volkswagen	-1.57	-1.60	-1.60	-1.56	-1.56	-1.52
	(2.17)	(2.15)	(2.14)	(2.13)	(2.18)	(2.17)
Model-years	409	409	409	409	409	409
Wald Chi²	78.85	84.13	82.73	84.20	77.54	86.92

Standard errors in parentheses, + p<.10, * p<.05, **p<01, ***p<.001

Figure 8: Interaction Term Graphs

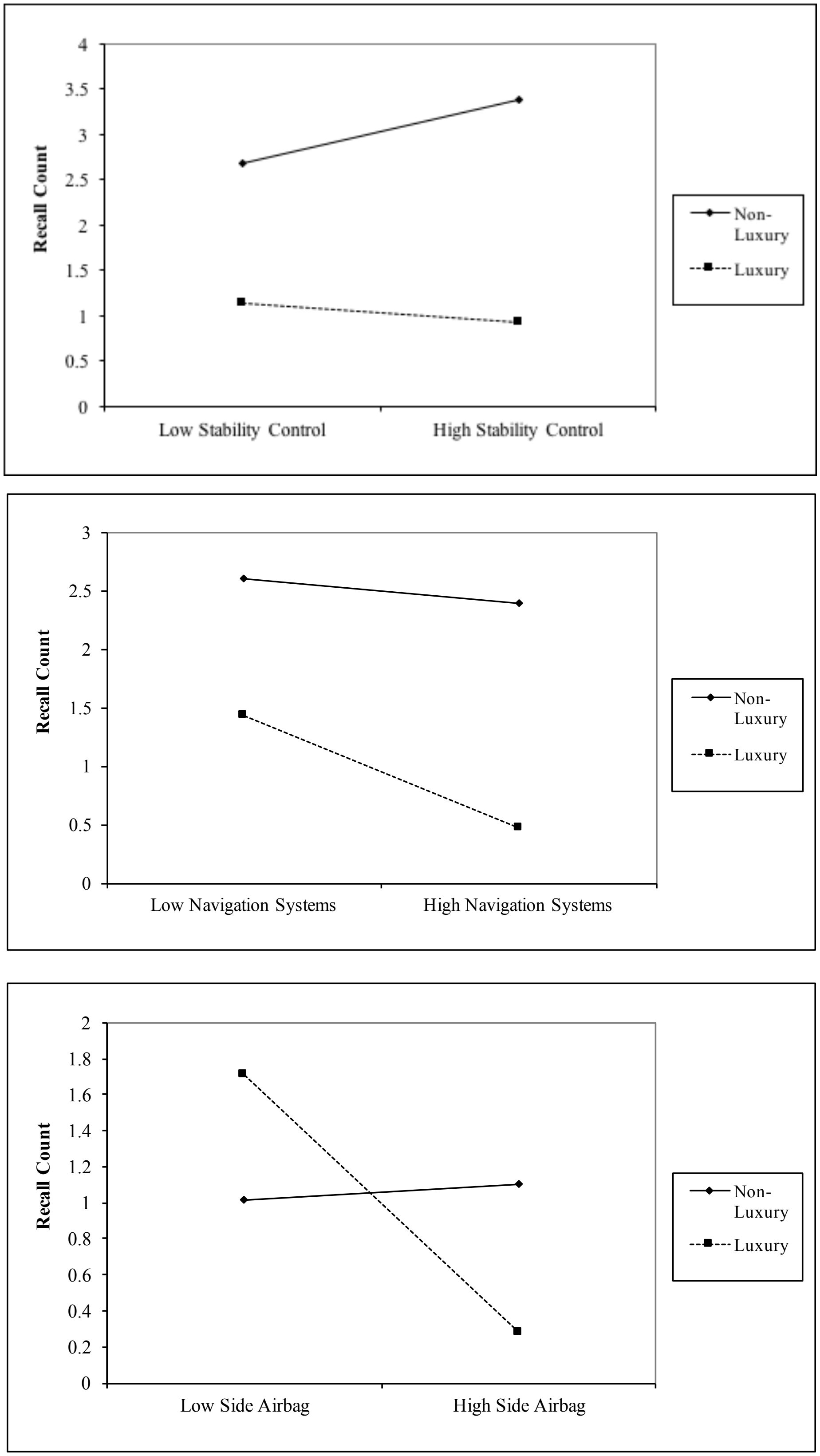


Table 9: Robustness Checks—Recall Count

	Panel Regression	Negative Binomial Panel	D-K Autocorrelation Panel	Autocorrelation Panel	GEE Panel
	1	2	3	4	5
Stability Control	0.65+	0.24+	0.69+	0.50	0.64+
	(0.34)	(0.13)	(0.37)	(0.34)	-0.35
Navigation Systems	-2.33*	-1.25**	-3.02**	-2.35*	-2.39**
	(0.94)	(0.43)	(0.90)	(0.94)	-0.9
Side Airbags	-0.27	-0.07	-0.21	0.16	-0.31
	(0.31)	(0.12)	(0.63)	(0.33)	-0.31
Volume	0.40**	0.16**	0.67**	0.40***	0.45***
	(0.12)	(0.05)	(0.20)	(0.12)	-0.12
Years Since Launch	-0.02+	-0.01	-0.01+	-0.02	-0.02+
	(0.01)	(0.01)	(0.01)	(0.01)	-0.01
2003	-3.14	-0.86	-2.45***	-2.66	-2.98
	(2.28)	(0.79)	(0.20)	(2.11)	-2.08
2004	0.18	0.06	0.31***	0.12	0.21
	(0.33)	(0.11)	(0.06)	(0.27)	-0.34
2005	0.27	0.09	0.51***	0.18	0.33
	(0.34)	(0.12)	(0.09)	(0.33)	-0.35
2006	-0.07	-0.01	0.37***	-0.20	0.02
	(0.37)	(0.13)	(0.09)	(0.37)	-0.38
2007	-0.22	-0.03	0.31	-0.24	-0.11
	(0.36)	(0.13)	(0.20)	(0.38)	-0.37
2008	-0.78*	-0.20	-0.30	-0.82*	-0.67+
	(0.38)	(0.14)	(0.27)	(0.40)	-0.38
2009	-0.68	-0.17	-0.01	-0.76+	-0.54
	(0.42)	(0.16)	(0.44)	(0.44)	-0.42
2010	-0.59	-0.13	0.02	-0.62	-0.45
	(0.48)	(0.18)	(0.54)	(0.49)	-0.47
2011	2.20	0.63	2.11***	1.80	2.17
	(2.32)	(0.80)	(0.54)	(2.14)	-2.12
Luxury	0.08	0.05	0.72*	-0.04	0.2
	(0.56)	(0.22)	(0.31)	(0.51)	-0.48
Chrysler	-1.13	-0.30	0.16	-1.22	-0.88
	(1.87)	(0.71)	(1.00)	(1.69)	-1.57
Ford	-2.15	-0.64	-1.86+	-2.60	-2.15
	(1.84)	(0.70)	(0.94)	(1.67)	-1.54
GM	-1.49	-0.37	-0.58	-1.76	-1.37
	(1.82)	(0.69)	(0.99)	(1.64)	-1.52
Honda	-0.10	0.03	-0.08	-0.74	-0.11
	(2.04)	(0.78)	(0.90)	(1.82)	-1.69
Mazda	1.47	0.27	2.11*	0.87	1.57
	(2.48)	(0.94)	(0.90)	(2.18)	-2.05
Mitsubishi	-1.92	-0.62	-1.53+	-2.47	-1.87
	(2.17)	(0.84)	(0.82)	(1.93)	-1.81
Nissan	-1.93	-0.62	-1.63	-2.63	-1.89
	(1.98)	(0.76)	(1.02)	(1.79)	-1.66
Toyota	-0.56	-0.12	0.19	-1.09	-0.45
	(1.91)	(0.73)	(1.15)	(1.72)	-1.6
Volkswagen	-1.71	-0.47	-1.56*	-2.06	-1.69
	(2.17)	(0.83)	(0.73)	(1.97)	-1.81
Constant	0.91	15.93	-3.22*	1.12	0.25
	(2.36)	(274.43)	(1.62)	(2.20)	-2.11
Model-years	409	409	409	409	409
Wald Chi²	86.70	59.47		69.14	96.81

Standard errors in parentheses, + p<.10, * p<.05, **p<01, ***p<.001

NOTE: Hyundai is omitted, as it is the reference category